Quantifying the effect of COVID-19 on the Stock Market

Data Bootcamp Final By Philip Ding, Zhen Yu Yang, and Sophia Park

Question 1: Do COVID-19 death rates affect the stock market/industry indices?

In [ ]:
```
import pandas as pd
import numpy as np
from sklearn.cluster import AgglomerativeClustering as agglom
from scipy.spatial.distance import cdist as dist
from sklearn.cluster import KMeans as kmeans
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression as linreg
from sklearn.neighbors import KNeighborsRegressor as knn
from sklearn.ensemble import RandomForestRegressor as rf
from sklearn.datasets import load_iris
from sklearn.linear_model import LogisticRegression
import pandas as pd
import numpy as np
import datetime
import seaborn as sns
import matplotlib.pyplot as plt
from datetime import date
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure
import calendar
```

importing some packages

In [320]:
```
national = pd.read_csv('national-history.csv', error_bad_lines=False)
national2 = national.sort_values(by='date')
national2 = national2.set_index('date')
national
```

Out[320]:

	date	death	deathIncrease	inIcuCumulative	inIcuCurrently	hospitalizedIncrease
0	2020-12-06	273374.0	1138	31946.0	20145.0	2256
1	2020-12-05	272236.0	2445	31831.0	19950.0	3316
2	2020-12-04	269791.0	2563	31608.0	19858.0	4652
3	2020-12-03	267228.0	2706	31276.0	19723.0	5331
4	2020-12-02	264522.0	2733	31038.0	19680.0	5028
...	...	...	...	...	...	...
315	2020-01-26	NaN	0	NaN	NaN	0
316	2020-01-25	NaN	0	NaN	NaN	0
317	2020-01-24	NaN	0	NaN	NaN	0
318	2020-01-23	NaN	0	NaN	NaN	0
319	2020-01-22	NaN	0	NaN	NaN	0

320 rows × 18 columns

A national dataset of covid deaths per day, along with other covid statistics from https://covidtracking.com/data/download (https://covidtracking.com/data/download)

In [321]:
```
industry = pd.read_csv('5_Industry_Portfolios_Daily.csv', error_bad_li
nes=False)
industry = industry.rename(columns={"Unnamed: 0": "date"})
industry['date'] = pd.to_datetime(industry['date'], format='%Y%m%d')
national['date'] = pd.to_datetime(national['date'])
industry
```

Out[321]:

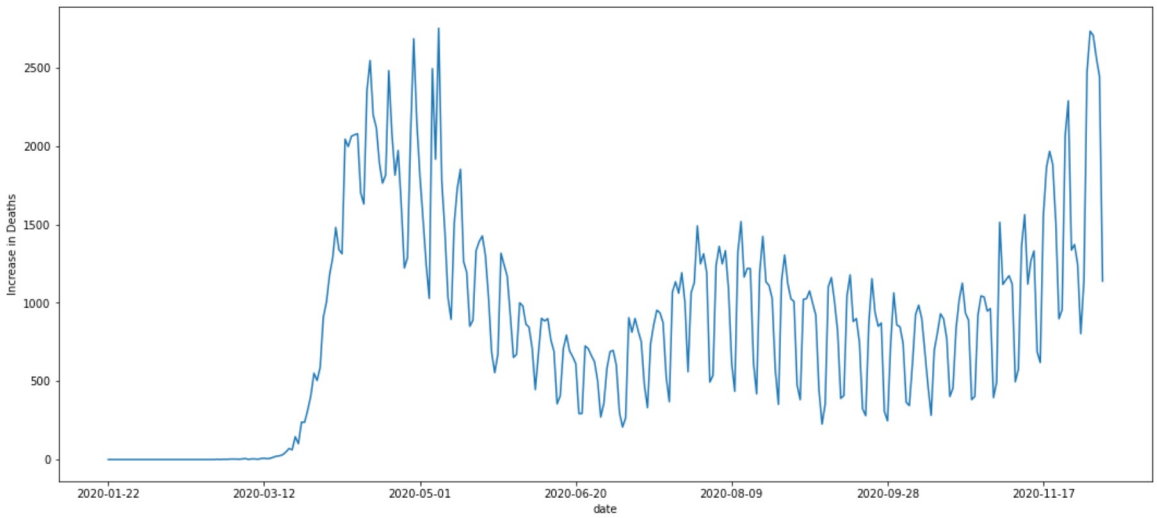
	date	Cnsmr	Manuf	HiTec	Hlth	Other
0	1926-07-01	-0.08	0.22	-0.11	0.97	0.21
1	1926-07-02	0.46	0.69	0.31	0.13	0.11
2	1926-07-06	0.27	0.28	0.32	0.23	-0.19
3	1926-07-07	-0.01	0.11	0.12	0.33	0.15
4	1926-07-08	0.24	0.09	0.38	0.91	0.39
...	...	...	...	...	...	...
24849	2020-10-26	-1.30	-1.88	-2.11	-1.06	-2.37
24850	2020-10-27	0.38	-1.13	0.53	-0.59	-1.64
24851	2020-10-28	-3.12	-3.13	-3.91	-3.01	-3.12
24852	2020-10-29	0.59	1.23	1.81	-0.15	0.94
24853	2020-10-30	-2.46	-0.48	-2.03	-0.76	-0.28

24854 rows × 6 columns

Industry data taken from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html) Also converting dates to datetime format

In [322]:
```
figure(figsize=(18,8))
plt.ylabel('Increase in Deaths')
national2['deathIncrease'].plot()
```

Out[322]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x24646dc4520>
```

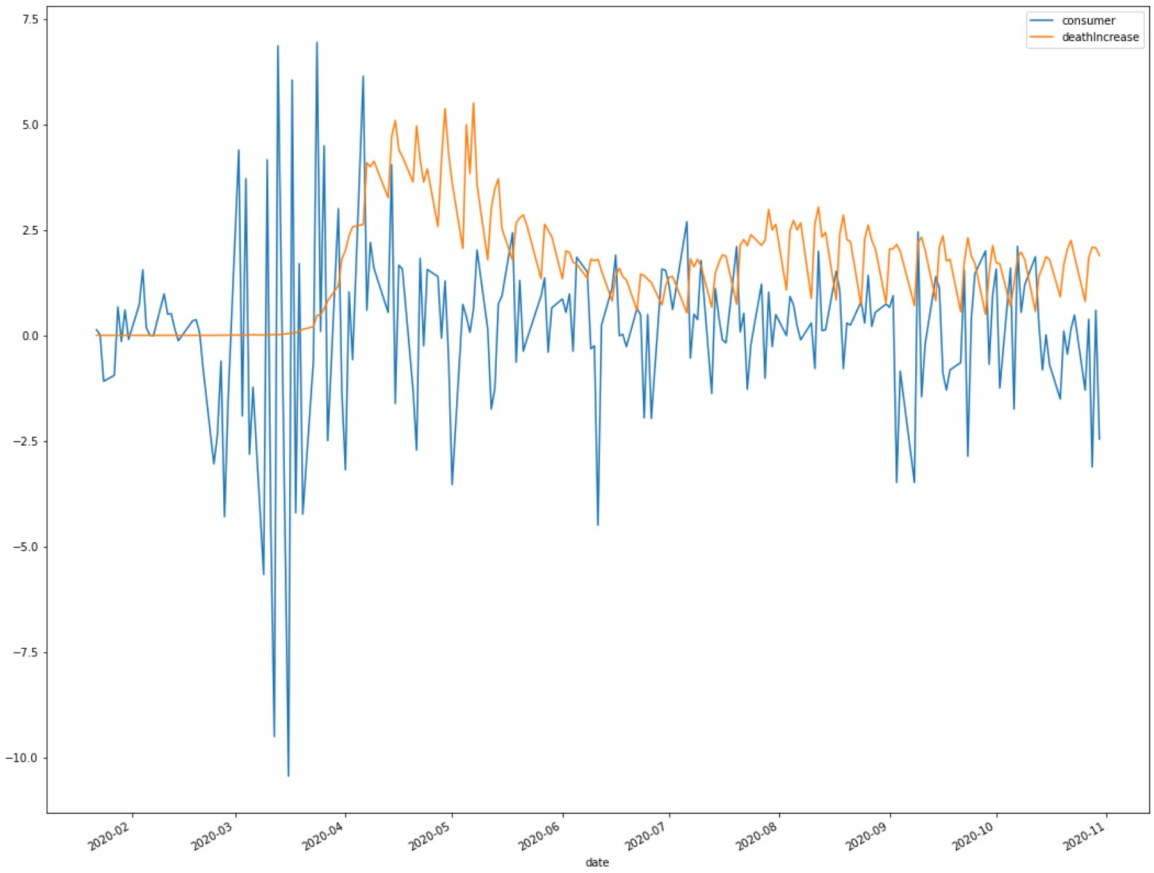


Quick plot of part of the data that we are analyzing. It is intersting to note the fluctuation in death increase - this could perhaps be explained by some phenomenon in sampling (for instance, maybe some states only periodically report their deaths).

In [323]:
```
combined = industry
combined = combined.join(national.set_index('date'), on='date')
combined = combined[combined['deathIncrease'].notna()]
combined.set_index('date')
combined = combined.rename(columns={"Cnsmr": "consumer"})
combined["deathIncrease"] = pd.to_numeric(combined["deathIncrease"], d
owncast="float")
new_columns = combined.columns.values;
new_columns[4] = 'health';
combined.columns  = new_columns
industry.set_index('date')
industry = industry.rename(columns={"Cnsmr": "consumer"})
new_columns = industry.columns.values;
new_columns[4] = 'health';
industry.columns  = new_columns
```

In [324]:
```
combined2 = combined.filter(['date','consumer','deathIncrease'])
combined2 = combined2.set_index('date')
combined2['deathIncrease'] = combined2['deathIncrease']/500
fig, ax = plt.subplots()
combined2.plot(ax=ax,kind='line',figsize = (18,15))
```

Out[324]: <matplotlib.axes._subplots.AxesSubplot at 0x24644be4580>



We can see from this graph immediately that the behavior and movement of stock indices looks at a cursory glance to operate differently from covid graphs - however, some of the bumps look visually to correlate

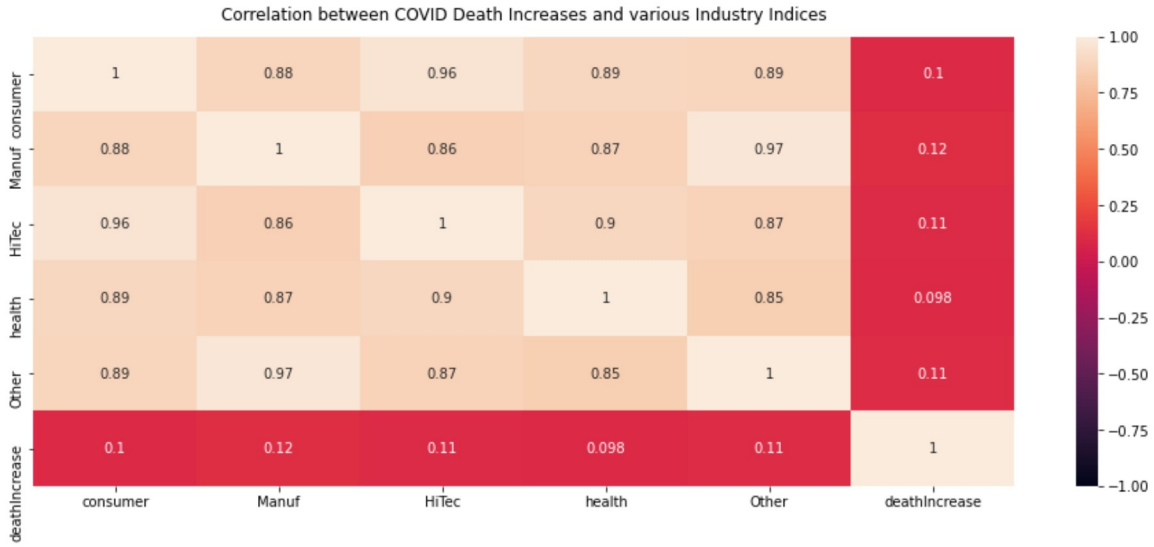
In [325]:
```
combined2 = combined.filter(['date','consumer','Manuf', 'HiTec', 'heal
th', 'Other', 'deathIncrease'])
combined2.corr()
```

Out[325]:

	consumer	Manuf	HiTec	health	Other	deathIncrease
consumer	1.000000	0.884822	0.958101	0.892906	0.885299	0.100900
Manuf	0.884822	1.000000	0.856809	0.871784	0.971035	0.117534
HiTec	0.958101	0.856809	1.000000	0.895201	0.868297	0.106578
health	0.892906	0.871784	0.895201	1.000000	0.850384	0.097926
Other	0.885299	0.971035	0.868297	0.850384	1.000000	0.109409
deathIncrease	0.100900	0.117534	0.106578	0.097926	0.109409	1.000000

The correlation of death increase and the five indices is very weak. This was expected, as the two inherently move in different ways - pandemics are somewhat consistently growing, while indices vary positive/negative with high variance day by day.

In [326]:
```
#corr = combined2.corr()
#fig = plt.figure()
#ax = fig.add_subplot(111)
#cax = ax.matshow(corr,cmap='coolwarm', vmin=-1, vmax=1)
#fig.colorbar(cax)
#ticks = np.arange(0,len(combined2.columns),1)
#ax.set_xticks(ticks)
#plt.xticks(rotation=90)
#ax.set_yticks(ticks)
#ax.set_xticklabels(combined2.columns)
#ax.set_yticklabels(combined2.columns)
#plt.show()
#my matplotlib heatmap broke, not sure why, didn't change anything - h
ere's an SNS heatmap instead

plt.figure(figsize=(16, 6))
heatmap = sns.heatmap(combined2.corr(), vmin=-1, vmax=1, annot=True)
heatmap.set_title('Correlation between COVID Death Increases and vario
us Industry Indices', fontdict={'fontsize':12}, pad=12);
```



A visualization of the aforementioned lack of correlation - the indices correspond heavily to each other, but hardly have a correlation with increase in deaths

In [327]:
```
combined['deltadeathincrease'] = combined['deathIncrease'] - combined
['deathIncrease'].shift(-1)
combined['delta2deathincrease'] = combined['deltadeathincrease'] / com
bined['deltadeathincrease'].shift(-1)
```

Making two new variables - the difference and ratio of the change of the difference in death increase. These measurements should behave in ways more similar to the stock market indices, and it would not be surprising to see a negative correlation here with deltadeathincrease - given that a decrease in death rate seems like it would correlate with a rise in stocks and vice versa. Similarly with delta2deathincrease - perhaps trends of decreasing/increasing correspond with large shifts in stock indices.

In [328]:
```
combined_corr = combined.replace([np.inf, -np.inf], np.nan)
combined_corr = combined_corr[combined_corr['delta2deathincrease'].not
na()]
column_1 = combined_corr['consumer']

column_2 = combined_corr['delta2deathincrease']

consumer_corr = column_1.corr(column_2)
Manuf_corr = combined_corr['Manuf'].corr(combined_corr['delta2deathinc
rease'])
HiTec_corr = combined_corr['HiTec'].corr(combined_corr['delta2deathinc
rease'])
health_corr = combined_corr['health'].corr(combined_corr['delta2deathi
ncrease'])
```

In [329]:
```
combined2_corr = combined.replace([np.inf, -np.inf], np.nan)
combined2_corr = combined_corr[combined_corr['deltadeathincrease'].not
na()]
consumer_corr2 = combined_corr['consumer'].corr(combined_corr['deltade
athincrease'])
Manuf_corr2 = combined_corr['Manuf'].corr(combined_corr['deltadeathinc
rease'])
HiTec_corr2 = combined_corr['HiTec'].corr(combined_corr['deltadeathinc
rease'])
health_corr2 = combined_corr['health'].corr(combined_corr['deltadeathi
ncrease'])
```

In [330]:
```
print ("Consumer, Manufacturing, High Tech, and Health Correlations ar
e:")
print (consumer_corr2, Manuf_corr2, HiTec_corr2, health_corr2)
```

```
Consumer, Manufacturing, High Tech, and Health Correlations are:
-0.07143423843153361 -0.00289854973086498 -0.039908750439652974 -0.01
65566516199145
```

In [331]:
```
import numpy as np
import scipy.stats
manuf_r, manuf_p = scipy.stats.pearsonr(combined_corr['Manuf'], combin
ed_corr['delta2deathincrease'])
consumer_r, consumer_p = scipy.stats.pearsonr(combined_corr['consumer
'], combined_corr['delta2deathincrease'])
hitec_r, hitec_p = scipy.stats.pearsonr(combined_corr['HiTec'], combin
ed_corr['delta2deathincrease'])
health_r, health_p = scipy.stats.pearsonr(combined_corr['health'], com
bined_corr['delta2deathincrease'])
```

In [332]:
```
print ("P value for manufacturing is: ", manuf_p)
print ("P value for consumer is: ", consumer_p)
print ("P value for high tech is: ", hitec_p)
print ("P value for health is: ", health_p)
```

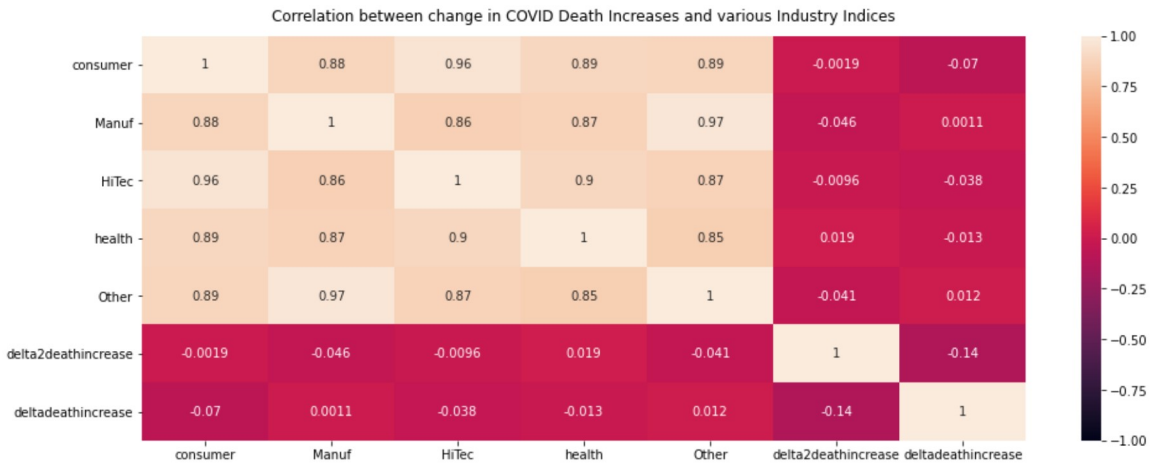
```
P value for manufacturing is:  0.5482061896123934
P value for consumer is:  0.9802369802092401
P value for high tech is:  0.9004182231056465
P value for health is:  0.8066375742344323
```

In [333]:
```
combined3 = combined.filter(['date','consumer','Manuf', 'HiTec', 'heal
th', 'Other','delta2deathincrease', 'deltadeathincrease'])
corr = combined3.corr()
corr
```

Out[333]:

	consumer	Manuf	HiTec	health	Other	delta2deathincrease
consumer	1.000000	0.884822	0.958101	0.892906	0.885299	-0.001903
Manuf	0.884822	1.000000	0.856809	0.871784	0.971035	-0.046096
HiTec	0.958101	0.856809	1.000000	0.895201	0.868297	-0.009611
health	0.892906	0.871784	0.895201	1.000000	0.850384	0.018799
Other	0.885299	0.971035	0.868297	0.850384	1.000000	-0.041322
delta2deathincrease	-0.001903	-0.046096	-0.009611	0.018799	-0.041322	1.000000
deltadeathincrease	-0.070049	0.001057	-0.037854	-0.013057	0.011611	-0.135215

In [334]:
```
combined3 = combined.filter(['date','consumer','Manuf', 'HiTec', 'heal
th', 'Other','delta2deathincrease', 'deltadeathincrease'])
corr = combined3.corr()
# fig = plt.figure()
# ax = fig.add_subplot(111)
# cax = ax.matshow(corr,cmap='coolwarm', vmin=-1, vmax=1)
# fig.colorbar(cax)
# ticks = np.arange(0,len(combined3.columns),1)
# ax.set_xticks(ticks)
# plt.xticks(rotation=90)
# ax.set_yticks(ticks)
# ax.set_xticklabels(combined3.columns)
# ax.set_yticklabels(combined3.columns)
# plt.show()
#again, my matplotlib visualization broke and I'm not sure why. Here's
a SNS visualization that does the same thing
plt.figure(figsize=(16, 6))
heatmap = sns.heatmap(combined3.corr(), vmin=-1, vmax=1, annot=True)
heatmap.set_title('Correlation between change in COVID Death Increases
and various Industry Indices', fontdict={'fontsize':12}, pad=12);
```



Neither the correlations or the p values are strong between any of these measures and the industry indices. This reinforces the observation during the pandemic that the deaths perhaps don't really affect the stock market, given the record highs of the S&P contrasted to the high death rates.

Question 2: We would still expect the stock market to respond in some way to COVID, but maybe death rates aren't the best indicator of financial markets. Can we predict behavior of indices with public opinion of COVID, as opposed to quantitative data on the pandemic? We will investigate this question by looking at Google Trends data

In [335]:
```
vaccine = pd.read_csv('vaccine-stats.csv', error_bad_lines=False)
vaccine = vaccine.drop(vaccine.index[0])

vaccine.reset_index(level=0, inplace=True)
vaccine = vaccine.rename(columns={vaccine.columns[0]: 'date'})
vaccine = vaccine.rename(columns={vaccine.columns[1]: 'searches'})
vaccine['date'] = pd.to_datetime(vaccine['date'])
vaccine['date'] = pd.DatetimeIndex(vaccine['date']) + pd.DateOffset(1)
vaccine = vaccine.set_index('date')
vaccine_join = combined.join(vaccine, on='date')
vaccine_join["searches"] = pd.to_numeric(vaccine_join["searches"], dow
ncast="float")
vaccine_join = vaccine_join[vaccine_join['searches'].notna()]

vaccine_join
```

Out[335]:

	date	consumer	Manuf	HiTec	health	Other	death	deathIncrease	inIcuCun
24659	2020-01-27	-0.95	-1.54	-2.06	-0.29	-1.81	NaN	0.0	
24664	2020-02-03	0.72	0.25	1.16	1.21	0.73	NaN	0.0	
24669	2020-02-10	0.98	0.20	1.12	0.65	0.39	0.0	0.0	
24678	2020-02-24	-3.05	-3.06	-3.79	-2.42	-3.63	0.0	0.0	
24683	2020-03-02	4.39	4.04	4.58	4.21	4.15	11.0	3.0	
24688	2020-03-09	-5.67	-10.04	-7.22	-5.67	-9.63	35.0	4.0	
24693	2020-03-16	-10.45	-11.59	-12.61	-9.74	-13.38	100.0	21.0	
24698	2020-03-23	-0.60	-5.02	-0.90	-3.82	-4.75	582.0	101.0	
24703	2020-03-30	3.00	2.59	3.77	4.65	2.08	3425.0	588.0	
24708	2020-04-06	6.14	6.92	7.90	5.07	7.94	11932.0	1313.0	
24712	2020-04-13	0.54	-2.20	0.12	-0.93	-2.85	25516.0	1630.0	
24717	2020-04-20	-1.29	-3.05	-1.36	-0.04	-2.15	40199.0	1815.0	
24722	2020-04-27	1.39	1.78	1.04	1.19	3.35	52684.0	1287.0	
24727	2020-05-04	0.73	0.44	1.01	0.55	-0.48	65209.0	1028.0	
24732	2020-05-11	0.15	-1.09	0.64	2.38	-1.60	77534.0	894.0	
24737	2020-05-18	2.43	5.67	2.34	1.31	5.24	86823.0	889.0	
24746	2020-06-01	0.86	0.87	0.39	-1.07	0.84	101187.0	671.0	
24751	2020-06-08	1.50	2.46	0.81	0.79	1.55	106708.0	676.0	
24756	2020-06-15	1.13	0.87	1.15	0.71	1.06	111606.0	406.0	
24761	2020-06-22	0.64	0.37	1.39	-0.11	0.10	115653.0	294.0	
24766	2020-06-29	1.57	2.52	1.32	0.61	1.75	119503.0	358.0	
24770	2020-07-06	2.69	0.58	1.81	0.72	1.64	122847.0	266.0	
24775	2020-07-13	-1.38	-0.11	-2.28	-0.21	-0.19	127843.0	331.0	
24780	2020-07-20	2.10	-1.09	2.25	0.23	-0.39	133100.0	369.0	
24785	2020-07-27	1.21	0.16	1.46	1.11	-0.11	140186.0	1065.0	
24790	2020-08-03	-0.01	0.18	1.82	1.49	0.52	147588.0	536.0	
24795	2020-08-10	0.29	1.72	-0.44	-0.52	0.90	154901.0	435.0	
24800	2020-08-17	1.52	-0.33	0.59	1.29	-0.66	162380.0	419.0	
24805	2020-08-24	0.80	1.76	0.74	-0.48	1.64	169197.0	352.0	
24810	2020-08-31	0.74	-1.04	0.33	0.58	-1.15	175656.0	382.0	
24819	2020-09-14	1.39	1.26	1.51	2.36	1.71	186609.0	408.0	
24824	2020-09-21	-0.65	-2.35	0.26	-1.92	-2.67	191962.0	280.0	
24829	2020-09-28	2.00	1.41	1.64	0.70	2.06	197193.0	247.0	
24834	2020-10-05	1.59	1.89	2.11	2.40	1.67	202147.0	344.0	
24839	2020-10-12	1.86	0.49	2.51	0.56	0.72	206996.0	282.0	

	date	consumer	Manuf	HiTec	health	Other	death	deathIncrease	inIcuCun
24844	2020-10-19	-1.51	-1.24	-1.67	-1.60	-1.48	211959.0	456.0	
24849	2020-10-26	-1.30	-1.88	-2.11	-1.06	-2.37	217549.0	402.0	

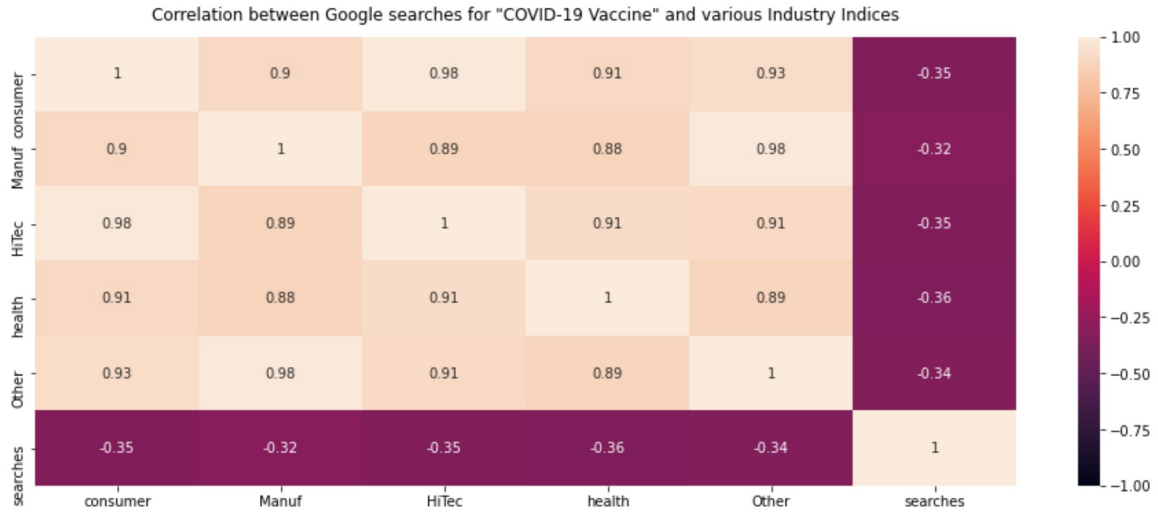
Cleaning and preparing Google Trends data on the popularity of searches for "COVID-19 vaccine" in the US

In [336]:
```
vaccine_join = vaccine_join.filter(['date','consumer','Manuf', 'HiTec
', 'health', 'Other','searches'])
vaccine_join.corr()
```

Out[336]:

	consumer	Manuf	HiTec	health	Other	searches
consumer	1.000000	0.904207	0.981283	0.905916	0.927635	-0.349824
Manuf	0.904207	1.000000	0.889230	0.876513	0.984918	-0.316990
HiTec	0.981283	0.889230	1.000000	0.914344	0.913988	-0.350070
health	0.905916	0.876513	0.914344	1.000000	0.889743	-0.357535
Other	0.927635	0.984918	0.913988	0.889743	1.000000	-0.337576
searches	-0.349824	-0.316990	-0.350070	-0.357535	-0.337576	1.000000

In [337]:
```
# corr = vaccine_join.corr()
# fig = plt.figure()
# ax = fig.add_subplot(111)
# cax = ax.matshow(corr,cmap='coolwarm', vmin=-1, vmax=1)
# fig.colorbar(cax)
# ticks = np.arange(0,len(vaccine_join.columns),1)
# ax.set_xticks(ticks)
# plt.xticks(rotation=90)
# ax.set_yticks(ticks)
# ax.set_xticklabels(vaccine_join.columns)
# ax.set_yticklabels(vaccine_join.columns)
# plt.show()
# same as last two heatmaps
plt.figure(figsize=(16, 6))
heatmap = sns.heatmap(vaccine_join.corr(), vmin=-1, vmax=1, annot=True)
heatmap.set_title('Correlation between Google searches for "COVID-19 Vaccine" and various Industry Indices', fontdict={'fontsize':12}, pad=12);
```



Correlations between Google searches for "COVID-19 Vaccine" and the stock indices are immediately much higher than between COVID-19 deaths and the indices

In [338]:
```
import scipy.stats
manuf_search_r, manuf_search_p = scipy.stats.pearsonr(vaccine_join['Manuf'], vaccine_join['searches'])
consumer_search_r, consumer_search_p = scipy.stats.pearsonr(vaccine_join['consumer'], vaccine_join['searches'])
hitec_search_r, hitec_search_p = scipy.stats.pearsonr(vaccine_join['HiTec'], vaccine_join['searches'])
health_search_r, health_search_p = scipy.stats.pearsonr(vaccine_join['health'], vaccine_join['searches'])
other_search_r, other_search_p = scipy.stats.pearsonr(vaccine_join['Other'], vaccine_join['searches'])
```

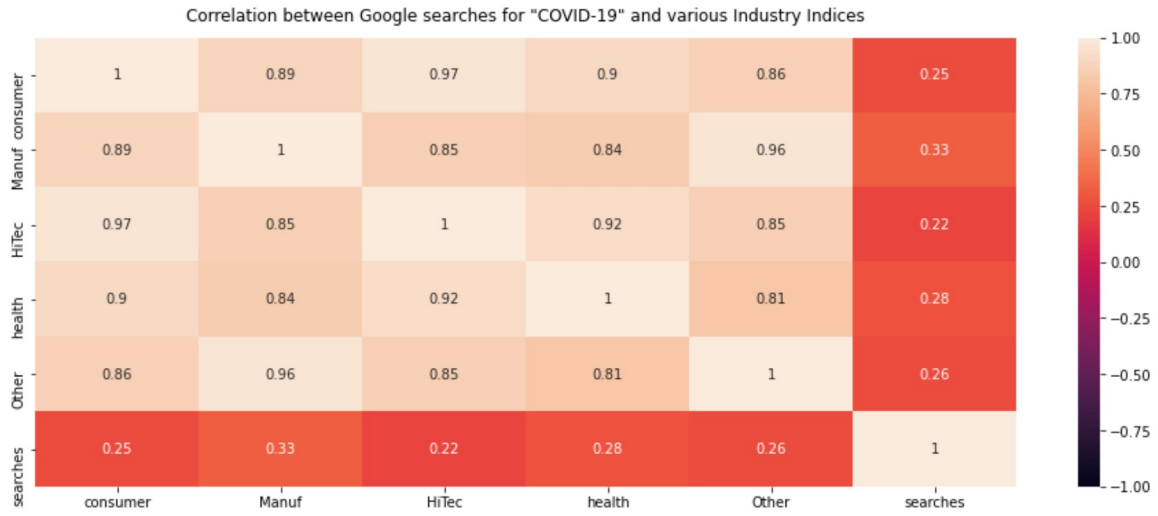
In [339]:
```
print ("P value for manufacturing is: ", manuf_search_p)
print ("P value for consumer is: ", consumer_search_p)
print ("P value for high tech is: ", hitec_search_p)
print ("P value for health is: ", health_search_p)
print ("P value for health is: ", other_search_p)
```

```
P value for manufacturing is:  0.05592495067816227
P value for consumer is:  0.033801084447746196
P value for high tech is:  0.03366751263041661
P value for health is:  0.029815245720317105
P value for health is:  0.0410193612189759
```

All of these P values are low, indicating a high possibility of a correlation. However, it is interesting to note that the magnitude of the correlations are all similar, with no distinctly different impact on one sector over the others (one might expect health to be most strongly, for example). All correlations are negative as well, which is interesting, as one might expect more news about vaccines to lead to upticks in the stock market.

In [340]:
```
covid_19 = pd.read_csv('covid-19-stats.csv', error_bad_lines=False)
covid_19 = vaccine.drop(vaccine.index[0])

covid_19.reset_index(level=0, inplace=True)
covid_19 = covid_19.rename(columns={covid_19.columns[0]: 'date'})
covid_19 = covid_19.rename(columns={covid_19.columns[1]: 'searches'})
covid_19['date'] = pd.to_datetime(covid_19['date'])
covid_19['date'] = pd.DatetimeIndex(covid_19['date']) + pd.DateOffset
(1)
#this offset is necessary because google trends is every sunday
#while index trends are not on sundays
covid_19 = covid_19.set_index('date')
covid_19_join = combined.join(covid_19, on='date')
covid_19_join["searches"] = pd.to_numeric(covid_19_join["searches"], d
owncast="float")

covid_19_join = covid_19_join[covid_19_join['searches'].notna()]
```

In [341]:
```
covid_19_join = covid_19_join.filter(['date','consumer','Manuf', 'HiTe
c', 'health', 'Other','searches'])
# corr = covid_19_join.corr()
# fig = plt.figure()
# ax = fig.add_subplot(111)
# cax = ax.matshow(corr,cmap='coolwarm', vmin=-1, vmax=1)
# fig.colorbar(cax)
# ticks = np.arange(0,len(vaccine_join.columns),1)
# ax.set_xticks(ticks)
# plt.xticks(rotation=90)
# ax.set_yticks(ticks)
# ax.set_xticklabels(vaccine_join.columns)
# ax.set_yticklabels(vaccine_join.columns)
# plt.show()
# same as previous two - this visualization broke so I did it in seabo
rn

plt.figure(figsize=(16, 6))
heatmap = sns.heatmap(covid_19_join.corr(), vmin=-1, vmax=1, annot=Tru
e)
heatmap.set_title('Correlation between Google searches for "COVID-19"
and various Industry Indices', fontdict={'fontsize':12}, pad=12);
```



In [342]:
```
import scipy.stats
manuf_covid_search_r, manuf_covid_search_p = scipy.stats.pearsonr(covi
d_19_join['Manuf'], covid_19_join['searches'])
consumer_covid_search_r, consumer_covid_search_p = scipy.stats.pearson
r(covid_19_join['consumer'], covid_19_join['searches'])
hitec_covid_search_r, hitec_covid_search_p = scipy.stats.pearsonr(covi
d_19_join['HiTec'], covid_19_join['searches'])
health_covid_search_r, health_covid_search_p = scipy.stats.pearsonr(co
vid_19_join['health'], covid_19_join['searches'])
other_covid_search_r, other_covid_search_p = scipy.stats.pearsonr(covi
d_19_join['Other'], covid_19_join['searches'])
print ("P value for manufacturing is: ", manuf_covid_search_p)
print ("P value for consumer is: ", consumer_covid_search_p)
print ("P value for high tech is: ", hitec_covid_search_p)
print ("P value for health is: ", health_covid_search_p)
print ("P value for health is: ", other_covid_search_p)
```

```
P value for manufacturing is:  0.039985413126394496
P value for consumer is:  0.11456209817451413
P value for high tech is:  0.1688826720428412
P value for health is:  0.08154265584897492
P value for health is:  0.10946594575383622
```

The correlation between searches for "COVID-19" and the indices is of a smaller degree than "COVID-19 Vaccine", positive instead of negative, and has larger P values. To prevent P-hacking, we picked these two specific search terms to analyze beforehand and did not leave out any other correlation analysis.

Question 3: Are confounding factors causing the correlation between Google searches and the indices?

To gauge the possibility of confounding factors, we are going to examine the correlation of the data with two control group, in this case the 2008/2011 US recessions (caused by the housing crisis and the Euro crisis). This helps us examine whether there is some outside factor unaccounted for - for example, perhaps the shape of the Google Trends data coincidentally matches the normal shape of the stock market during a recession. If there is a low P-value between these trends and these recessions where there was no COVID, it would indicate that the correlation is likely caused by some confounding variable

Question 3a) The Euro Crisis

In [343]:
```
MEUR = industry[industry['date'].dt.year == 2011]
meurcontrol = MEUR

meurcontrol['date'] = pd.DatetimeIndex(MEUR['date']) + pd.DateOffset(y
ears = 9)

#again, this is to make merging the data easier.
mask = (meurcontrol['date'] > '2020-1-27') & (meurcontrol['date'] <= '
2020-10-28')
#filtering for the dates in the 2020 dataset
meurcontrol = (meurcontrol.loc[mask])
meurcontrol['date'] = pd.DatetimeIndex(meurcontrol['date']) + pd.DateO
ffset(1)
#offset of two because the days of week need to line up
meur_vaccine_join = meurcontrol.join(vaccine, on='date')
meur_vaccine_join["searches"] = pd.to_numeric(meur_vaccine_join["searc
hes"], downcast="float")
meur_vaccine_join = meur_vaccine_join[meur_vaccine_join['searches'].no
tna()]
```

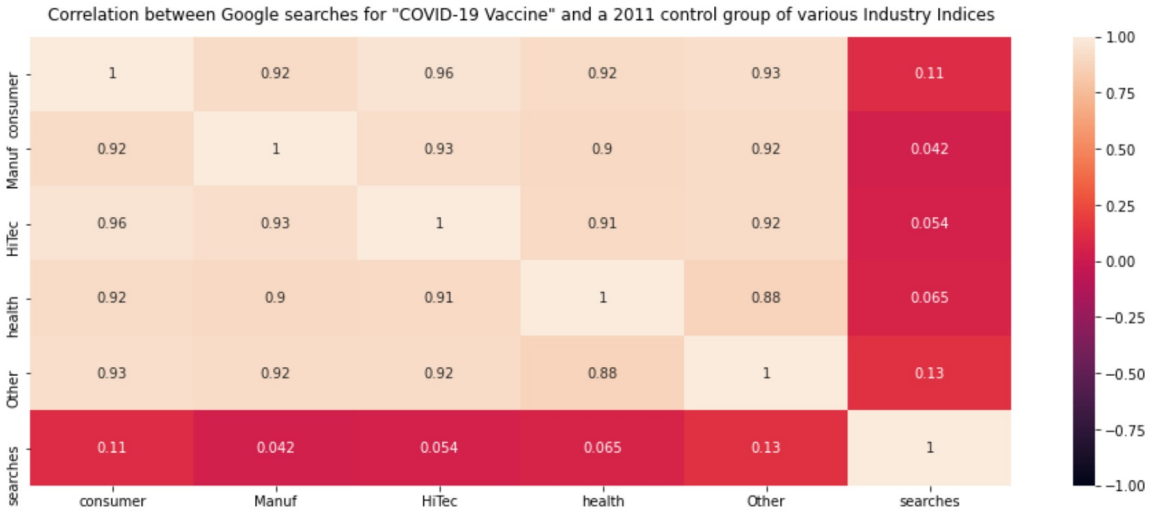
```
<ipython-input-343-f5007df0d461>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/panda
s-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  meurcontrol['date'] = pd.DatetimeIndex(MEUR['date']) + pd.DateOffse
t(years = 9)
<ipython-input-343-f5007df0d461>:10: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/panda
s-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  meurcontrol['date'] = pd.DatetimeIndex(meurcontrol['date']) + pd.Da
teOffset(1)
```

In [344]:
```
meur_vaccine_join.corr()
```

Out[344]:

	consumer	Manuf	HiTec	health	Other	searches
consumer	1.000000	0.919177	0.959284	0.917024	0.932144	0.114442
Manuf	0.919177	1.000000	0.933654	0.901830	0.918984	0.041710
HiTec	0.959284	0.933654	1.000000	0.906481	0.917323	0.054267
health	0.917024	0.901830	0.906481	1.000000	0.879432	0.064651
Other	0.932144	0.918984	0.917323	0.879432	1.000000	0.133327
searches	0.114442	0.041710	0.054267	0.064651	0.133327	1.000000

In [345]:
```
plt.figure(figsize=(16, 6))
heatmap = sns.heatmap(meur_vaccine_join.corr(), vmin=-1, vmax=1, annot
=True)
heatmap.set_title('Correlation between Google searches for "COVID-19 V
accine" and a 2011 control group of various Industry Indices', fontdic
t={'fontsize':12}, pad=12);
```



In [346]:
```
meur_manuf_search_r, meur_manuf_search_p = scipy.stats.pearsonr(meur_v
accine_join['Manuf'], meur_vaccine_join['searches'])
meur_consumer_search_r, meur_consumer_search_p = scipy.stats.pearsonr
(meur_vaccine_join['consumer'], meur_vaccine_join['searches'])
meur_hitec_search_r, meur_hitec_search_p = scipy.stats.pearsonr(meur_v
accine_join['HiTec'], meur_vaccine_join['searches'])
meur_health_search_r, meur_health_search_p = scipy.stats.pearsonr(meur
_vaccine_join['health'], meur_vaccine_join['searches'])
meur_other_search_r, meur_other_search_p = scipy.stats.pearsonr(meur_v
accine_join['Other'], meur_vaccine_join['searches'])
```

In [347]:
```
print ("P value for manufacturing is: ", meur_manuf_search_p)
print ("P value for consumer is: ", meur_consumer_search_p)
print ("P value for high tech is: ", meur_hitec_search_p)
print ("P value for health is: ", meur_health_search_p)
print ("P value for health is: ", meur_other_search_p)
```

```
P value for manufacturing is:  0.8009527491928099
P value for consumer is:  0.4878564261657712
P value for high tech is:  0.7428252703046058
P value for health is:  0.6957830136254716
P value for health is:  0.4184234866970589
```

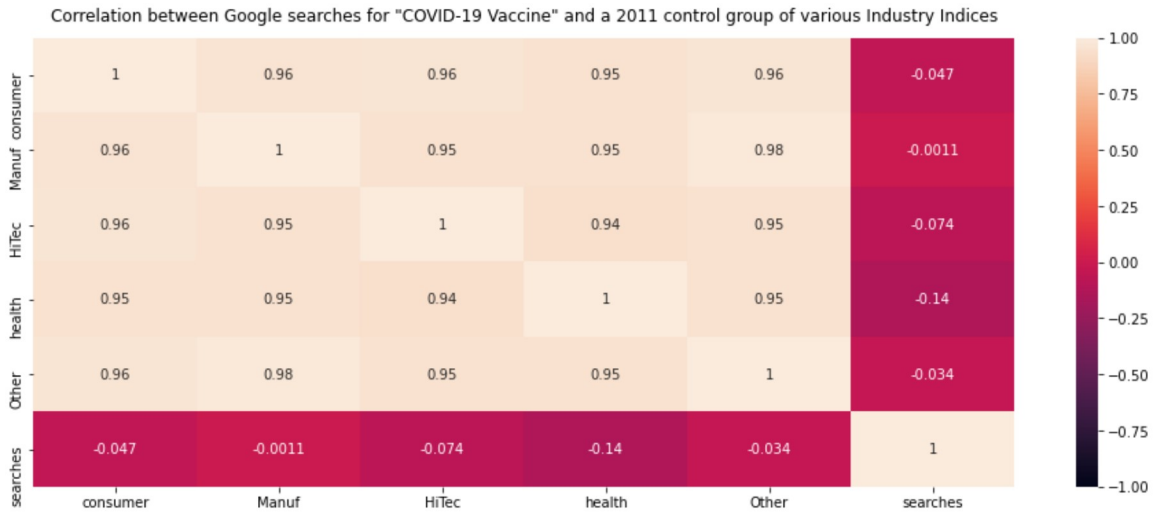
In [348]:
```
meur2 = industry
meur2['date'] = pd.DatetimeIndex(meur2['date']) + pd.DateOffset(3094)
mask = (meur2['date'] > '2020-1-27') & (meur2['date'] <= '2020-10-28')
#3094 days between the start of the 2011 US stock market crash and the
start of the COVID-19 Market crash

meur2 = (meur2.loc[mask])

meur_vaccine_join = meur2.join(vaccine, on='date')
meur_vaccine_join["searches"] = pd.to_numeric(meur_vaccine_join["searc
hes"], downcast="float")
meur_vaccine_join = meur_vaccine_join[meur_vaccine_join['searches'].no
tna()]
```

In [349]:
```
meur_vaccine_join.corr()
```

Out[349]:

	consumer	Manuf	HiTec	health	Other	searches
consumer	1.000000	0.957784	0.962347	0.952854	0.963421	-0.047401
Manuf	0.957784	1.000000	0.950972	0.951427	0.976973	-0.001138
HiTec	0.962347	0.950972	1.000000	0.941522	0.951234	-0.074499
health	0.952854	0.951427	0.941522	1.000000	0.947849	-0.135498
Other	0.963421	0.976973	0.951234	0.947849	1.000000	-0.033643
searches	-0.047401	-0.001138	-0.074499	-0.135498	-0.033643	1.000000

In [350]:
```
plt.figure(figsize=(16, 6))
heatmap = sns.heatmap(meur_vaccine_join.corr(), vmin=-1, vmax=1, annot
=True)
heatmap.set_title('Correlation between Google searches for "COVID-19 V
accine" and a 2011 control group of various Industry Indices', fontdic
t={'fontsize':12}, pad=12);
```



In [351]:
```
meur_manuf_search_r, meur_manuf_search_p = scipy.stats.pearsonr(meur_v
accine_join['Manuf'], meur_vaccine_join['searches'])
meur_consumer_search_r, meur_consumer_search_p = scipy.stats.pearsonr
(meur_vaccine_join['consumer'], meur_vaccine_join['searches'])
meur_hitec_search_r, meur_hitec_search_p = scipy.stats.pearsonr(meur_v
accine_join['HiTec'], meur_vaccine_join['searches'])
meur_health_search_r, meur_health_search_p = scipy.stats.pearsonr(meur
_vaccine_join['health'], meur_vaccine_join['searches'])
meur_other_search_r, meur_other_search_p = scipy.stats.pearsonr(meur_v
accine_join['Other'], meur_vaccine_join['searches'])
```

In [352]:
```
print ("P value for manufacturing is: ", meur_manuf_search_p)
print ("P value for consumer is: ", meur_consumer_search_p)
print ("P value for high tech is: ", meur_hitec_search_p)
print ("P value for health is: ", meur_health_search_p)
print ("P value for health is: ", meur_other_search_p)
```

```
P value for manufacturing is:  0.9949024119030181
P value for consumer is:  0.7900823078420238
P value for high tech is:  0.6754087389989661
P value for health is:  0.44483062329478323
P value for health is:  0.8501811037293296
```

Question 3b) Global Financial Crisis

In [353]:
```
gfc = industry[industry['date'].dt.year == 2008]
gfccontrol = gfc

gfccontrol['date'] = pd.DatetimeIndex(gfc['date']) + pd.DateOffset(yea
rs = 12)
#again, this is to make merging the data easier.
mask = (gfccontrol['date'] > '2020-1-27') & (gfccontrol['date'] <= '20
20-10-28')
#filtering for the dates in the 2020 dataset
gfccontrol = (gfccontrol.loc[mask])
gfccontrol['date'] = pd.DatetimeIndex(gfccontrol['date']) + pd.DateOff
set(2)
#offset because the days of week need to line up
gfc_vaccine_join = gfccontrol.join(vaccine, on='date')
gfc_vaccine_join["searches"] = pd.to_numeric(gfc_vaccine_join["searche
s"], downcast="float")
gfc_vaccine_join = gfc_vaccine_join[gfc_vaccine_join['searches'].notna
()]
```

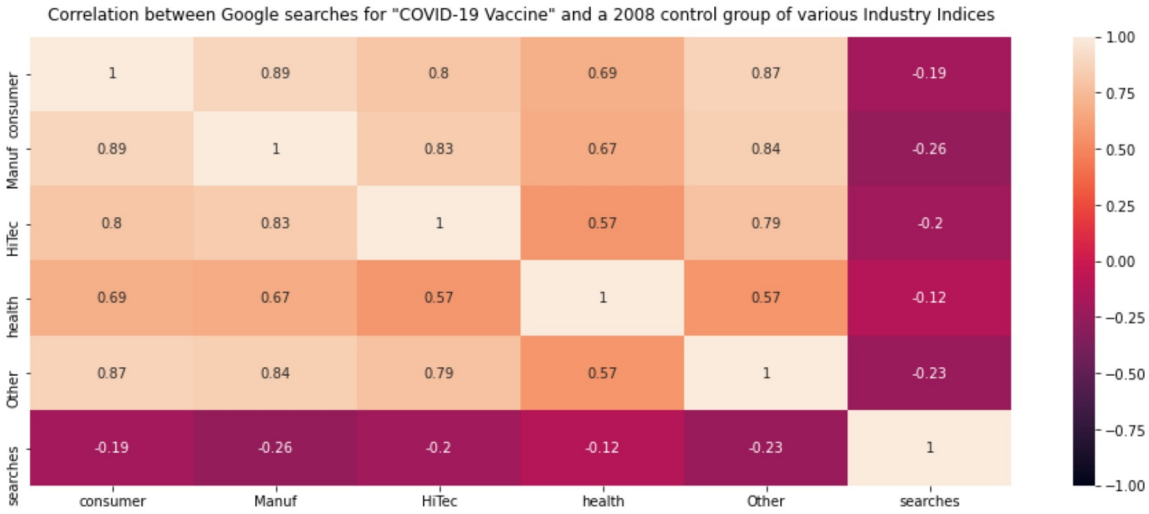
```
<ipython-input-353-fa126a0f598d>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/panda
s-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  gfccontrol['date'] = pd.DatetimeIndex(gfc['date']) + pd.DateOffset
(years = 12)
<ipython-input-353-fa126a0f598d>:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/panda
s-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  gfccontrol['date'] = pd.DatetimeIndex(gfccontrol['date']) + pd.Date
Offset(2)
```

In [354]:
```
gfc_vaccine_join.corr()
```

Out[354]:

	consumer	Manuf	HiTec	health	Other	searches
consumer	1.000000	0.888627	0.802294	0.694194	0.870072	-0.189591
Manuf	0.888627	1.000000	0.829342	0.673827	0.844577	-0.257511
HiTec	0.802294	0.829342	1.000000	0.573718	0.786756	-0.197005
health	0.694194	0.673827	0.573718	1.000000	0.566212	-0.116514
Other	0.870072	0.844577	0.786756	0.566212	1.000000	-0.226700
searches	-0.189591	-0.257511	-0.197005	-0.116514	-0.226700	1.000000

In [355]:
```
plt.figure(figsize=(16, 6))
heatmap = sns.heatmap(gfc_vaccine_join.corr(), vmin=-1, vmax=1, annot=
True)
heatmap.set_title('Correlation between Google searches for "COVID-19 V
accine" and a 2008 control group of various Industry Indices', fontdic
t={'fontsize':12}, pad=12);
```



In [356]:
```
gfc_manuf_search_r, gfc_manuf_search_p = scipy.stats.pearsonr(gfc_vacc
ine_join['Manuf'], gfc_vaccine_join['searches'])
gfc_consumer_search_r, gfc_consumer_search_p = scipy.stats.pearsonr(gf
c_vaccine_join['consumer'], gfc_vaccine_join['searches'])
gfc_hitec_search_r, gfc_hitec_search_p = scipy.stats.pearsonr(gfc_vacc
ine_join['HiTec'], gfc_vaccine_join['searches'])
gfc_health_search_r, gfc_health_search_p = scipy.stats.pearsonr(gfc_va
ccine_join['health'], gfc_vaccine_join['searches'])
gfc_other_search_r,gfc_other_search_p = scipy.stats.pearsonr(gfc_vacci
ne_join['Other'], gfc_vaccine_join['searches'])
```

In [357]:
```
print ("P value for manufacturing is: ", gfc_manuf_search_p)
print ("P value for consumer is: ", gfc_consumer_search_p)
print ("P value for high tech is: ", gfc_hitec_search_p)
print ("P value for health is: ", gfc_health_search_p)
print ("P value for health is: ", gfc_other_search_p)
```

```
P value for manufacturing is:  0.12387829889880168
P value for consumer is:  0.2610625076152162
P value for high tech is:  0.2425227187470856
P value for health is:  0.49224164754387206
P value for health is:  0.17724892433707834
```

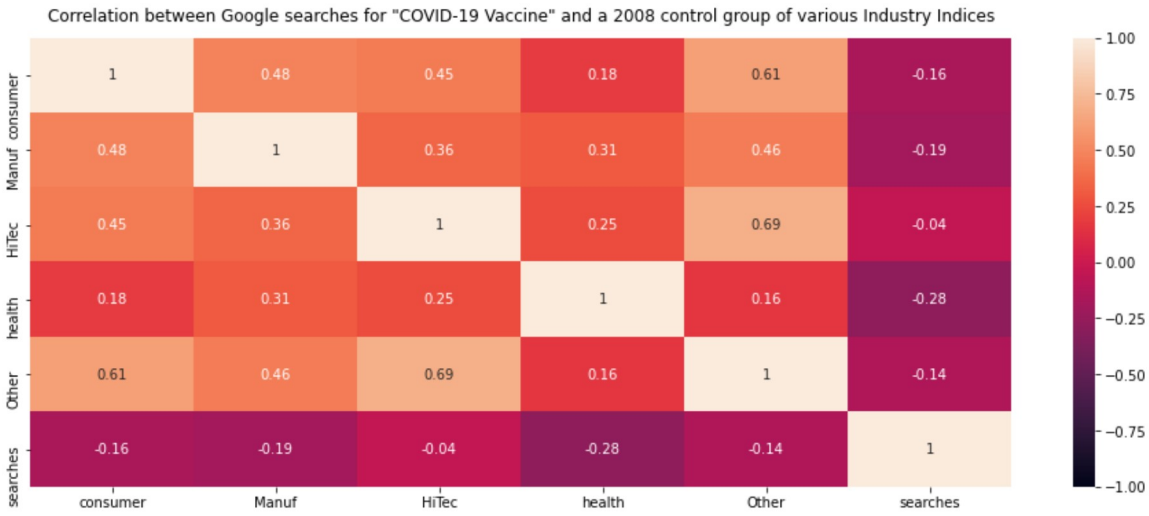
In [358]:
```
gfc2 = industry
gfc2['date'] = pd.DatetimeIndex(gfc2['date']) + pd.DateOffset(4150)
mask = (gfc2['date'] > '2020-1-27') & (gfc2['date'] <= '2020-10-28')
#4150 days between the start of the 2008 US stock market crash and the
start of the COVID-19 Market crash

gfc2 = (gfc2.loc[mask])

gfc_vaccine_join = gfc2.join(vaccine, on='date')
gfc_vaccine_join["searches"] = pd.to_numeric(gfc_vaccine_join["searche
s"], downcast="float")
gfc_vaccine_join = gfc_vaccine_join[gfc_vaccine_join['searches'].notna
()]
```

In [359]:
```
gfc_vaccine_join.corr()
```

Out[359]:

	consumer	Manuf	HiTec	health	Other	searches
consumer	1.000000	0.479713	0.445559	0.181513	0.612851	-0.156904
Manuf	0.479713	1.000000	0.355509	0.306615	0.455949	-0.189400
HiTec	0.445559	0.355509	1.000000	0.251323	0.691197	-0.040326
health	0.181513	0.306615	0.251323	1.000000	0.163966	-0.276614
Other	0.612851	0.455949	0.691197	0.163966	1.000000	-0.135216
searches	-0.156904	-0.189400	-0.040326	-0.276614	-0.135216	1.000000

In [360]:
```
plt.figure(figsize=(16, 6))
heatmap = sns.heatmap(gfc_vaccine_join.corr(), vmin=-1, vmax=1, annot=
True)
heatmap.set_title('Correlation between Google searches for "COVID-19 V
accine" and a 2008 control group of various Industry Indices', fontdic
t={'fontsize':12}, pad=12);
```



In [361]:
```
gfc_manuf_search_r, gfc_manuf_search_p = scipy.stats.pearsonr(gfc_vacc
ine_join['Manuf'], gfc_vaccine_join['searches'])
gfc_consumer_search_r, gfc_consumer_search_p = scipy.stats.pearsonr(gf
c_vaccine_join['consumer'], gfc_vaccine_join['searches'])
gfc_hitec_search_r, gfc_hitec_search_p = scipy.stats.pearsonr(gfc_vacc
ine_join['HiTec'], gfc_vaccine_join['searches'])
gfc_health_search_r, gfc_health_search_p = scipy.stats.pearsonr(gfc_va
ccine_join['health'], gfc_vaccine_join['searches'])
gfc_other_search_r,gfc_other_search_p = scipy.stats.pearsonr(gfc_vacci
ne_join['Other'], gfc_vaccine_join['searches'])
```

In [362]:
```
print ("P value for manufacturing is: ", gfc_manuf_search_p)
print ("P value for consumer is: ", gfc_consumer_search_p)
print ("P value for high tech is: ", gfc_hitec_search_p)
print ("P value for health is: ", gfc_health_search_p)
print ("P value for health is: ", gfc_other_search_p)
```

```
P value for manufacturing is:  0.25475147321916447
P value for consumer is:  0.3468299037396982
P value for high tech is:  0.8100380825275967
P value for health is:  0.09272670968012994
P value for health is:  0.4182806701750784
```

Question 3: Analysis

We analyzed vs control groups of the 2008 and 2011 financial market crashes. In both, we shifted them two ways: first, by looking at data from Jan. 27 - October 28 of the respective years, and also by looking at the first ten months of each recession (the same time period that we have for the 2020 recession). This is to investigate potentially confounding relationships between the Google search, these indices, and time based values or the natural shape of a recession (perhaps the search trends simply match the normal curve of a recession, or coincide with normal monthly stock market trends).

Looking at the P values - none of them in any scenario are as low as the ones from 2020. Additionally, the R values were lower as well. This is encouraging, as it eliminates a few sources of confounding and strengthens the connection between the Google searches for "COVID-19 Vaccine" and the change in market indices. We expect the same to hold true for the Google searches for "COVID-19", as the same potential confounding factors should be ruled out.

Potential confounding still exists. however, many general potential sources of it involving the general nature/shape of recessions can likely be eliminated.

Question 4: A deeper dive into specific companies and financial analysis

In [363]:
```
industry['date'] = pd.to_datetime(industry['date'], format='%Y%m%d')
national['date'] = pd.to_datetime(national['date'])
ind_cov = industry[industry['date'].dt.year == 2020]
ind_rec = industry.iloc[21602:21999, 0:5]
ind_eur = industry.iloc[22127:22881, 0:5]
combined = industry
combined = combined.join(national.set_index('date'), on='date')
combined = combined[combined['deathIncrease'].notna()]
```

In [364]:
```
cov_di = combined['deathIncrease']
cov_hi = combined['hospitalizedIncrease']
cov_pi = combined['positiveIncrease']
national_reg = national.iloc[::-1]
national_reg
```

Out[364]:

	date	death	deathIncrease	inIcuCumulative	inIcuCurrently	hospitalizedIncrease
319	2020-01-22	NaN	0	NaN	NaN	0
318	2020-01-23	NaN	0	NaN	NaN	0
317	2020-01-24	NaN	0	NaN	NaN	0
316	2020-01-25	NaN	0	NaN	NaN	0
315	2020-01-26	NaN	0	NaN	NaN	0
...	...	...	...	...	...	...
4	2020-12-02	264522.0	2733	31038.0	19680.0	5028
3	2020-12-03	267228.0	2706	31276.0	19723.0	5331
2	2020-12-04	269791.0	2563	31608.0	19858.0	4652
1	2020-12-05	272236.0	2445	31831.0	19950.0	3316
0	2020-12-06	273374.0	1138	31946.0	20145.0	2256

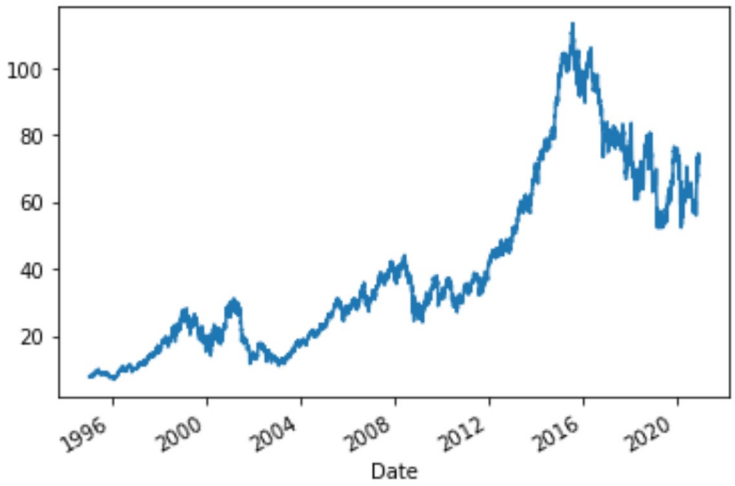
320 rows × 18 columns

In the line above, we looked at individual columns of the COVID-19 data as well as flipped the order of the data so it matches our stock market data

In [365]:
```
cvs = yf.download('CVS','1995-01-01','2020-12-12')
cvs_cov = yf.download('CVS','2020-01-01','2020-12-12')
cvs_eur = yf.download('CVS','2010-01-01','2012-12-31')
cvs_rec = yf.download('CVS','2007-12-01','2009-06-30')
cvs.Close.plot()
plt.show
```

```
[**********************100%**********************]  1 of 1 completed
[**********************100%**********************]  1 of 1 completed
[**********************100%**********************]  1 of 1 completed
[**********************100%**********************]  1 of 1 completed
```

Out[365]: <function matplotlib.pyplot.show(*args, **kw)>



In the above line, we download stock market data from CVS (healthcare industry) from Yahoo finance in a cumulative view (1995-2020) as well as different economic downturns such as the great recession (2007 - 2009), the European Debt Crisis (2010 - 2012) and the COVID-19 pandemic (2020). We graph the close price per trading day for the cumulative view of CVS above. This gives us a deeper look into a specific healthcare related company instead of looking at the general index for the healthcare industry.

In [366]:
```
cvs_eur.describe()
cvs_rec.describe()
cvs_cov.describe()
```

Out[366]:

	Open	High	Low	Close	Adj Close	Volume
count	240.000000	240.000000	240.000000	240.000000	240.000000	2.400000e+02
mean	64.013750	64.882125	63.094750	63.996167	63.059918	8.845602e+06
std	5.286630	5.098838	5.355556	5.254454	5.099349	4.236427e+06
min	53.630001	54.970001	52.040001	52.299999	51.031059	2.803700e+06
25%	59.772499	60.574999	59.209999	59.670000	59.083695	6.059400e+06
50%	63.795000	64.230000	62.850000	63.655001	62.720898	7.538300e+06
75%	67.287498	68.187502	66.402502	66.869999	66.242796	1.012930e+07
max	76.110001	76.440002	75.830002	76.050003	74.500000	3.442970e+07

In [367]:
```
cvs_cov.iloc[30:180, 0:5]
```

Out[367]:

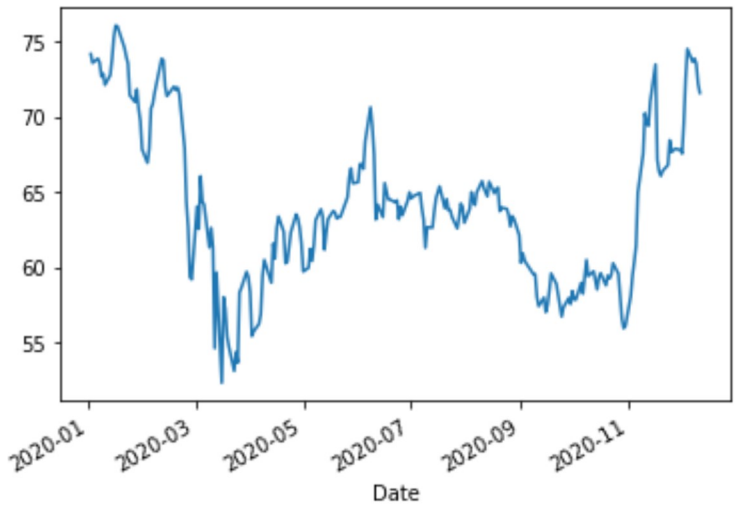
Date	Open	High	Low	Close	Adj Close
2020-02-14	71.980003	72.029999	70.269997	71.370003	69.638367
2020-02-18	71.190002	72.000000	70.900002	72.000000	70.253082
2020-02-19	72.309998	72.559998	71.660004	71.779999	70.038414
2020-02-20	71.500000	72.230003	70.559998	71.940002	70.194542
2020-02-21	71.550003	71.800003	71.010002	71.510002	69.774971
...	...	...	...	...	...
2020-09-11	58.130001	58.139999	57.060001	57.400002	56.917080
2020-09-14	57.630001	58.209999	57.549999	57.970001	57.482285
2020-09-15	58.000000	58.610001	56.990002	57.000000	56.520443
2020-09-16	57.200001	57.849998	56.099998	57.480000	56.996407
2020-09-17	57.099998	58.680000	56.820000	58.410000	57.918583

150 rows × 5 columns

The COVID-19 pandemic yielded the lowest standard deviation of stock prices (at close) compared to other economic downturns. this is expected for CVS as a healthcare company as a virus induced pandemic would see constant demand for CVS services. It is important to note though that comparing the February stock price for CVS with September prices we see a difference of much more than two standard deviations from the mean in both cases. Thus, the COVID-19 period is still a highly volatile time for CVS, as shown on the plot below.

In [368]:
```
cvs_cov.Close.plot()
plt.show
```

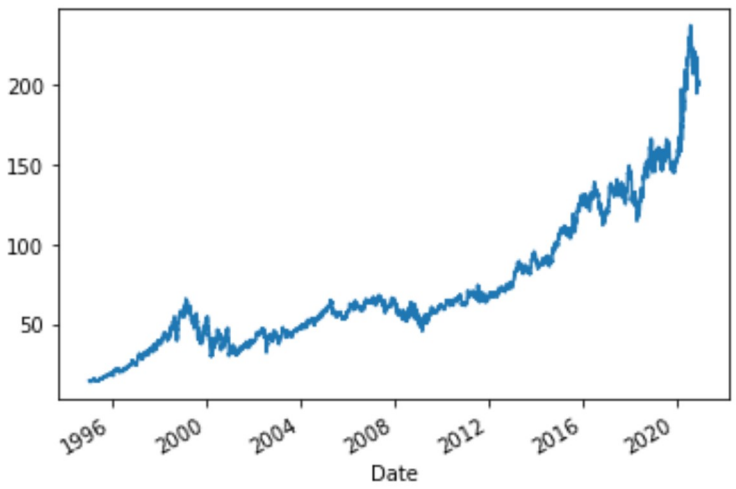
Out[368]: <function matplotlib.pyplot.show(*args, **kw)>



In [369]:
```
clx = yf.download('CLX','1995-01-01','2020-12-12')
clx_cov = yf.download('CLX','2020-01-01','2020-12-12')
clx_eur = yf.download('CLX','2010-01-01','2012-12-31')
clx_rec = yf.download('CLX','2007-12-01','2009-06-30')
clx.Close.plot()
plt.show
```

```
[**********************100%**********************]  1 of 1 completed
[**********************100%**********************]  1 of 1 completed
[**********************100%**********************]  1 of 1 completed
[**********************100%**********************]  1 of 1 completed
```

Out[369]: <function matplotlib.pyplot.show(*args, **kw)>



We also wanted to look at The Clorox Company as we thought it would yield interesting results given the high demand for its products during the COVID-19 pandemic. The process we used for CVS is repeated here. From first glance from this cumulative plot, it seems that The Clorox Company saw much more drastic increases in stock price during the COVID-19 pandemic compared with CVS.

In [370]:
```
clx_eur.describe()
clx_rec.describe()
clx_cov.describe()
```

Out[370]:

	Open	High	Low	Close	Adj Close	Volume
count	240.000000	240.000000	240.000000	240.000000	240.000000	2.400000e+02
mean	198.647125	201.285250	196.313374	198.726708	196.928154	1.757035e+06
std	23.457422	23.427932	23.459126	23.359126	23.947761	1.067079e+06
min	151.779999	153.009995	150.949997	151.520004	148.196564	4.895000e+05
25%	177.597504	182.327496	173.947498	177.504993	174.769737	1.070150e+06
50%	204.534996	207.480003	202.629997	204.589996	203.063934	1.498700e+06
75%	215.547504	218.002499	213.162502	215.025005	213.870422	2.084550e+06
max	238.190002	239.869995	235.610001	237.740005	236.518463	7.478700e+06

In [371]:
```
clx_cov.iloc[30:180, 0:5]
```

Out[371]:

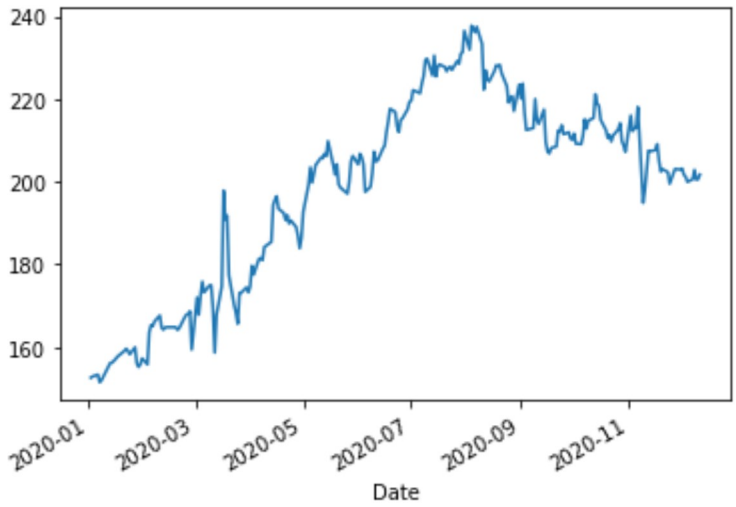
Date	Open	High	Low	Close	Adj Close
2020-02-14	164.990005	165.100006	164.190002	164.830002	162.290070
2020-02-18	165.259995	165.360001	163.860001	164.820007	162.280228
2020-02-19	165.000000	165.720001	164.100006	164.839996	162.299911
2020-02-20	164.729996	164.970001	163.589996	164.169998	161.640228
2020-02-21	163.690002	165.270004	163.690002	164.639999	162.102997
...	...	...	...	...	...
2020-09-11	215.479996	216.419998	212.119995	214.000000	212.900436
2020-09-14	214.490005	217.929993	213.500000	217.460007	216.342667
2020-09-15	215.679993	216.389999	208.679993	209.589996	208.513092
2020-09-16	209.160004	210.949997	206.899994	207.350006	206.284607
2020-09-17	206.669998	208.990005	204.660004	206.850006	205.787170

150 rows × 5 columns

While the European Debt Crisis and the great recession yielded standard deviations of 3.8 and 4.2 respectively, COVID-19 standard deviation for The Clorox Company was significantly higher at 23.4 (all figures are for close prices). This increased volatility is not surprising as demand for products from the company increased heavily during the pandemic. For example, the close price in February compared to September (shown above) was vastly different. This tells us that while economic downturns affects the entire stock market, the causes of such downturns still creats winners in each unique case. The Clorox Company, compared with other economic downturns, was positively impacted by the COVID-19 crisis and saw its volatility translate into signficant gains for the company. A plot below is shown to highlight these gains.

In [372]:
```
clx_cov.Close.plot()
plt.show
```

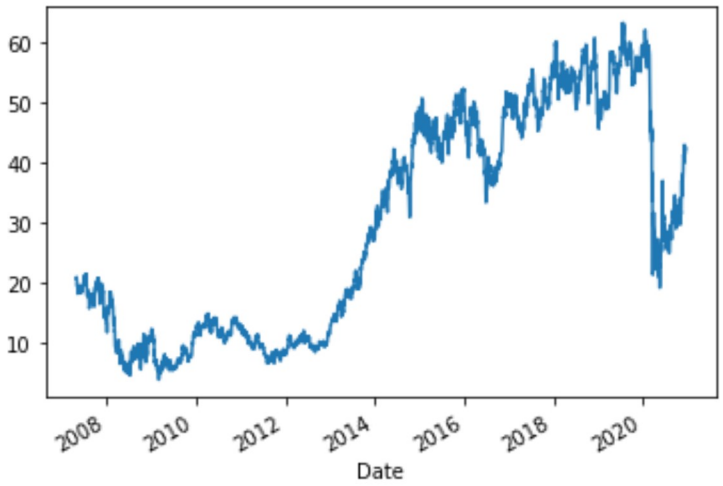
Out[372]:
```
<function matplotlib.pyplot.show(*args, **kw)>
```



In [373]:
```
dal = yf.download('DAL','1995-01-01','2020-12-12')
dal_cov = yf.download('DAL','2020-01-01','2020-12-12')
dal_eur = yf.download('DAL','2010-01-01','2012-12-31')
dal_rec = yf.download('DAL','2007-12-01','2009-06-30')
dal.Close.plot()
plt.show
```

```
[**********************100%**********************]  1 of 1 completed
[**********************100%**********************]  1 of 1 completed
[**********************100%**********************]  1 of 1 completed
[**********************100%**********************]  1 of 1 completed
```

Out[373]: <function matplotlib.pyplot.show(*args, **kw)>



Finally, we wanted to look at Delta Airlines as airlines are traditionally hit the hardest as a part of this pandemic. The process we used for CVS and The Clorox Company is repeated here. From this cumulative plot, we can see that while 2008 and 2012 showed declines in stock price, Delta Airlines was hit the hardest in 2020 with the steepest drop.

In [374]:
```
dal_eur.describe()
dal_rec.describe()
dal_cov.describe()
```

Out[374]:

	Open	High	Low	Close	Adj Close	Volume
count	240.000000	240.000000	240.000000	240.000000	240.000000	2.400000e+02
mean	34.814375	35.573667	33.828333	34.681792	34.628023	3.085508e+07
std	11.765146	11.729216	11.797150	11.787662	11.677469	2.395423e+07
min	18.799999	19.540001	17.510000	19.190001	19.190001	3.810100e+06
25%	26.650000	27.295000	25.925000	26.702500	26.702500	1.454168e+07
50%	30.925000	31.565001	30.125000	30.835000	30.835000	2.233950e+07
75%	39.870001	41.052500	39.132501	40.032499	40.032499	4.244268e+07
max	62.130001	62.480000	61.869999	62.029999	61.604282	1.346265e+08

In [375]:
```
dal_cov.iloc[30:180, 0:5]
```

Out[375]:

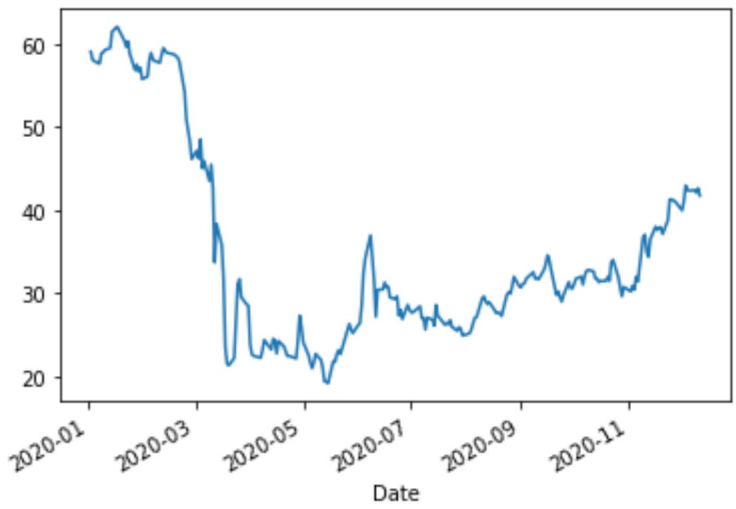
Date	Open	High	Low	Close	Adj Close
2020-02-14	59.240002	59.470001	58.580002	58.900002	58.495766
2020-02-18	58.869999	59.470001	58.410000	58.720001	58.317001
2020-02-19	58.490002	58.580002	58.029999	58.509998	58.509998
2020-02-20	58.200001	58.990002	58.119999	58.380001	58.380001
2020-02-21	57.959999	58.020000	56.869999	57.869999	57.869999
...	...	...	...	...	...
2020-09-11	31.809999	32.130001	31.340000	31.700001	31.700001
2020-09-14	32.290001	32.900002	32.009998	32.820000	32.820000
2020-09-15	33.200001	34.480000	33.099998	33.509998	33.509998
2020-09-16	33.799999	34.990002	33.189999	34.570000	34.570000
2020-09-17	33.970001	35.070000	33.639999	33.959999	33.959999

150 rows × 5 columns

Once again, the volatility of the stock price is significantly higher during the COVID-19 period compared with the other economic downturns. This once again shows that specific causes of economic downturns affect different companies. In this case, the volatility increase from COVID-19 in comparison with other recessions is a consequence of significant losses as opposed to gains. As shown above, the stock price for Delta Airlines in February was close to double what is was in September. A plot below will highlight the losses.

In [376]:
```
dal_cov.Close.plot()
plt.show
```

Out[376]:
```
<function matplotlib.pyplot.show(*args, **kw)>
```



Multiple Linear Regression Analysis

To further explore the relationship between these specific companies and the COVID-19 pandemic, we ran regressions on the COVID-19 stock market data versus different predictor variables from the national COVID-19 data.

In [377]:
```
cvs_reg = pd.merge(left=national_reg, left_on='date', right=cvs_cov, r
ight_on='Date')
cvs_reg
```

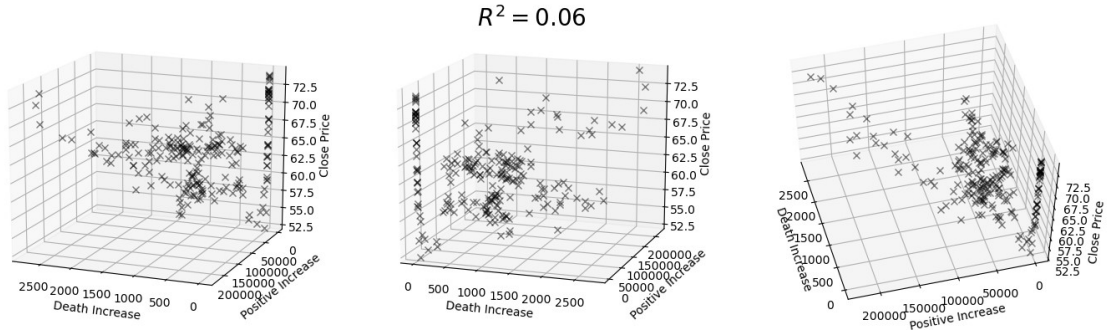
Out[377]:

	date	death	deathIncrease	inIcuCumulative	inIcuCurrently	hospitalizedIncrease
0	2020-01-22	NaN	0	NaN	NaN	0
1	2020-01-23	NaN	0	NaN	NaN	0
2	2020-01-24	NaN	0	NaN	NaN	0
3	2020-01-27	NaN	0	NaN	NaN	0
4	2020-01-28	NaN	0	NaN	NaN	0
...	...	...	...	...	...	...
217	2020-11-30	259316.0	1136	30469.0	18801.0	3394
218	2020-12-01	261789.0	2473	30749.0	19295.0	5222
219	2020-12-02	264522.0	2733	31038.0	19680.0	5028
220	2020-12-03	267228.0	2706	31276.0	19723.0	5331
221	2020-12-04	269791.0	2563	31608.0	19858.0	4652

222 rows × 24 columns

Because the stock market data and COVID-19 data starts on different dates and do not match (stock market data is only trading days while COVID-19 data is not), we merged them so that only the matching dates for both datasets are used.

In [378]:
```
from sklearn import linear_model
from mpl_toolkits.mplot3d import Axes3D

X = cvs_reg[['deathIncrease', 'positiveIncrease']].values.reshape(-1,
2)
Y = cvs_reg['Close']

x = X[:, 0]
y = X[:, 1]
z = Y

ols = linear_model.LinearRegression()
model = ols.fit(X, Y)

r2 = model.score(X, Y)

plt.style.use('default')

fig = plt.figure(figsize=(14, 4))

ax1 = fig.add_subplot(131, projection='3d')
ax2 = fig.add_subplot(132, projection='3d')
ax3 = fig.add_subplot(133, projection='3d')

axes = [ax1, ax2, ax3]

for ax in axes:
    ax.plot(x, y, z, color='black', zorder=14, linestyle='none', marke
r='x', alpha=0.5)
    ax.set_xlabel('Death Increase', fontsize=10)
    ax.set_ylabel('Positive Increase', fontsize=10)
    ax.set_zlabel('Close Price', fontsize=10)

ax1.view_init(elev=17, azim=112)
ax2.view_init(elev=16, azim=-71)
ax3.view_init(elev=55, azim=165)

fig.suptitle('$R^2 = %.2f$' % r2, fontsize=20)

fig.tight_layout()
```



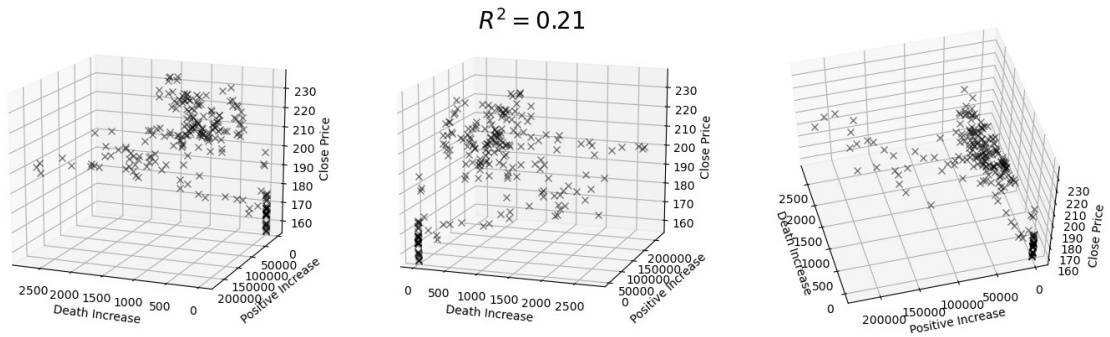
In [379]:
```
model.coef_
```

Out[379]:
```
array([-1.45625532e-03,  2.81835652e-05])
```

As shown above, we used number of death and positive case increases as predictor variables for the close price of CVS during the COVID-19 pandemic. A multiple linear regression was used. We find the coefficients to be, whether negative or positive, very close to zero and thus we conclude very limited predictive power. In the visualization of this regression, we also see an extremely small r-squared value which indicated no predictive power. This is surprising for us as we would have expected increased deaths from covid to drive sales of drugs and other medical supplies in CVS. However, it is possible that the economic lockdown had a more signnificant effect instead.

In [380]:
```
clx_reg = pd.merge(left=national_reg, left_on='date', right=clx_cov, r
ight_on='Date')
```

In [381]:
```
X = clx_reg[['deathIncrease', 'positiveIncrease']].values.reshape(-1,
2)
Y = clx_reg['Close']

x = X[:, 0]
y = X[:, 1]
z = Y

ols = linear_model.LinearRegression()
model = ols.fit(X, Y)

r2 = model.score(X, Y)

plt.style.use('default')

fig = plt.figure(figsize=(14, 4))

ax1 = fig.add_subplot(131, projection='3d')
ax2 = fig.add_subplot(132, projection='3d')
ax3 = fig.add_subplot(133, projection='3d')

axes = [ax1, ax2, ax3]

for ax in axes:
    ax.plot(x, y, z, color='black', zorder=14, linestyle='none', marke
r='x', alpha=0.5)
    ax.set_xlabel('Death Increase', fontsize=10)
    ax.set_ylabel('Positive Increase', fontsize=10)
    ax.set_zlabel('Close Price', fontsize=10)

ax1.view_init(elev=17, azim=112)
ax2.view_init(elev=16, azim=-71)
ax3.view_init(elev=55, azim=165)

fig.suptitle('$R^2 = %.2f$' % r2, fontsize=20)

fig.tight_layout()
```



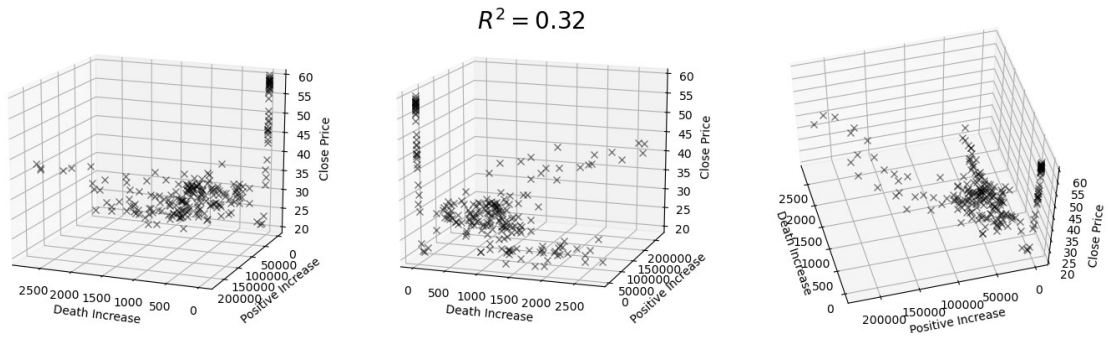
In [382]:
```
model.coef_
```

Out[382]:
```
array([0.00608884, 0.00015486])
```

As you can see, The Clorox Company showed higher coefficients compared to CVS and also a much higher r-squared. However, these values are still too low to conlcude that COVID-19 death or positive case increases had any predictive power on the stock price of the company. These results make sense to us as demand for cleaning products would increase with the worsening of COVID-19 but is probably more linked to things like the lockdowns and consumer panic for COVID-19 rather than actual deaths.

In [383]:
```
dal_reg = pd.merge(left=national_reg, left_on='date', right=dal_cov, r
ight_on='Date')
```

In [384]:
```
X = dal_reg[['deathIncrease', 'positiveIncrease']].values.reshape(-1,
2)
Y = dal_reg['Close']

x = X[:, 0]
y = X[:, 1]
z = Y

ols = linear_model.LinearRegression()
model = ols.fit(X, Y)

r2 = model.score(X, Y)

plt.style.use('default')

fig = plt.figure(figsize=(14, 4))

ax1 = fig.add_subplot(131, projection='3d')
ax2 = fig.add_subplot(132, projection='3d')
ax3 = fig.add_subplot(133, projection='3d')

axes = [ax1, ax2, ax3]

for ax in axes:
    ax.plot(x, y, z, color='black', zorder=14, linestyle='none', marke
r='x', alpha=0.5)
    ax.set_xlabel('Death Increase', fontsize=10)
    ax.set_ylabel('Positive Increase', fontsize=10)
    ax.set_zlabel('Close Price', fontsize=10)

ax1.view_init(elev=17, azim=112)
ax2.view_init(elev=16, azim=-71)
ax3.view_init(elev=55, azim=165)

fig.suptitle('$R^2 = %.2f$' % r2, fontsize=20)

fig.tight_layout()
```



In [385]:
```
model.coef_
```

Out[385]:
```
array([-9.89521743e-03,  5.09387964e-05])
```

Interestingly, the coefficients for Delta Airlines were quite low while the r-squared value was the highest out of all three regressions. We found this surprising because we would have imagined that the increase in positive test cases to be correlated to the demand for flights. However, it also makes sense that other factors like lockdowns and international travel regulations would have a bigger impact. Overall, it seems that COVID-19 factors itself have little to do with the stock of specific companies but rather the policies induced by COVID-19 that are impacting businesses the most.

Conclusion:

The COVID-19 pandemic's effect on the stock market is a hotly debated topic. From our analysis, we conclude that COVID-19 death rates have little impact on the stock market - what seems to be more important is public sentiment/interest (as seen by our Google trends data), and outside factors such as policies and innovations. We found that Google searches for "COVID-19 Vaccine" have a strong predictive power across all indices, as did searches "COVID-19", although P-values were higher for "COVID-19" than for "COVID-19 Vaccine", which had all 5 P-values under 0.05. We eliminated many possibilities for confounding factors by showing that these correlations do not apply to similar control groups.